Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 8 (2022) 623–627
www.elsevier.com/locate/egyr

The 8th International Conference on Energy and Environment Research ICEER 2021, 13–17 September

Dynamic remuneration of electricity consumers flexibility

Catarina Ribeiro[a], Tiago Pinto[a,*], Zita Vale[a], José Baptista[b]

[a] GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, School of Engineering of the Polytechnic of Porto (ISEP/IPP), Rua Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal

[b] University of Trás os Montes e Alto Douro (UTAD), INESC TEC—INESC Technology and Science (formerly INESC Porto, UTAD pole), Quinta de Prados, 5001-801 Vila Real, Portugal

Received 6 April 2022; accepted 21 April 2022
Available online 9 May 2022

Abstract

This paper proposes a decision support model to define electricity consumers' remuneration structures when providing consumption flexibility, optimized for different load regimes. The proposed model addresses the remuneration of consumers when participating in demand response programs, benefiting or penalizing those who adjust their consumption when needed. The model defines dynamic remuneration values with different natures for the aggregator (e.g. flexibility aggregator or curtailment service provider) and for the consumer. The preferences and perspective of both are considered, by incorporating variables that represent the energy price, the energy production and the flexibility of consumers. The validation is performed using real data from the Iberian market, and results enable to conclude that the proposed model adapts the remuneration values in a way that it is increased according to the consumers' elastic, while being reduced when the generation is higher. Consequently, the model boosts the active consumer participation when flexibility is required, while reaching a solution that represents an acceptable g tradeoff between the aggregators and the consumers.

Peer-review under responsibility of the scientific committee of the 8th International Conference on Energy and Environment Research, ICEER, 2021.

Keywords: Data mining; Decision support systems; Demand response; Dynamic pricing; Load profiling

1. Introduction

Power and energy systems are suffering major changes during the last years due to several factors such as the large integration of renewable energy sources, as incentivized by regulatory entities [1], the end of regulated monopolies and the introduction of free competition, particularly in the production and commercialization of electricity [2]. Electricity customers are free to choose and switch suppliers, seeking possible economic advantages. Potential benefits will depend on the efficient operation in the market and, on the other hand, the remuneration of aggregated players. The uncertainty brought by renewable energy sources' dependency on natural factors, such as solar intensity

* Corresponding author.
E-mail address: tcp@isep.ipp.pt (T. Pinto).

https://doi.org/10.1016/j.egyr.2022.04.056

Peer-review under responsibility of the scientific committee of the 8th International Conference on Energy and Environment Research, ICEER, 2021.

and wind speed, requires the system to use consumers' flexibility as a crucial means to balance the variation from the generation side [3,4]. However, adequate remuneration schemes for consumers' flexibility are still lacking. Consequently, the ability to engage the several involved parties, such as consumers, prosumers and different types of aggregators is weakened, and thereby postponing the generalized adoption of demand response programs.

Decision-support models in a context of electricity markets have already been proposed, e.g. [5,6]. The models focus mainly in consumers and generators' market negotiations, energy scheduling and planning, and the definition of demand response programs. The introduction of remuneration models for consumers' active participation are lacking, especially those that combine the perspective and potential advantages to both consumers and aggregators, while considering the needs from system. Some relevant works on consumer aggregation have been proposed, e.g. [7] which proposes a model for consumers' aggregation with the purpose of taking the most benefit from market participation, considering the perspective of both the system and the players'; and Raiker et al. [8] which considers a model for consumers and building energy resources' aggregation. However, specific models for defining the most suitable remuneration to e applied to different types of consumers depending on their characteristics and objectives; the needs from the system; and the perspective of the aggregator, are still lacking.

This paper presents a methodology for the dynamic definition of remuneration methods for consumers' flexibility when participating in demand response programs, benefiting those who adjust their consumption in times the system needs the most. The proposed model considers the perspective of both consumers and aggregators by balancing the remuneration values in a fair way. The remuneration model is validated using a case study based a real power network with 20 310 consumers and 548 distributed generators. Results show that the remuneration values enable boosting consumers' flexibility by incentivizing their active participation in times of need (i.e. when the consumption is high and generation is low) while using the reference market price as baseline.

After this introductory section, Section 2 presents the proposed consumers' flexibility model and Section 3 presents the results from the application of the proposed model. Finally, Section 4 presents the most relevant conclusions and contributions of the presented work, as well as directions for future work development.

2. Proposed model

The proposed model is directed to the demand response management from an aggregator. The Remuneration and Tariff Mechanism (RemT) [9,10] is a decision support mechanism that is being developed to support the Virtual Power Player (VPP) [11] actions in the definition of the best tariff and remuneration to apply to each of the aggregated players, regarding the VPP objectives and the individual goal of each aggregated player. The definition process is presented in Fig. 1.

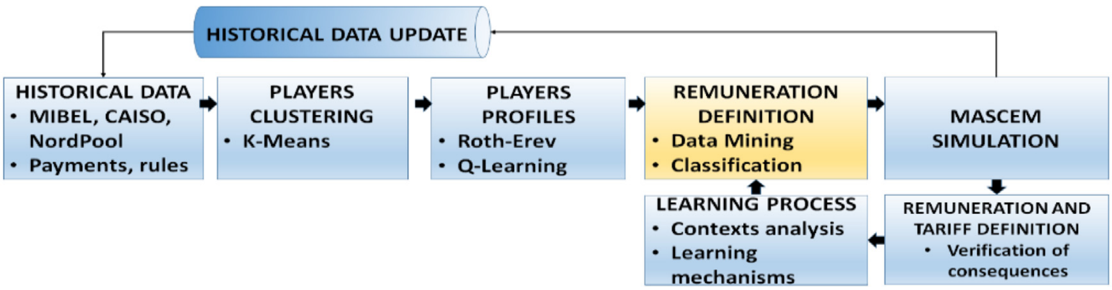

Fig. 1. RemT definition process [10].

In a first step, consumers are clustered based on the relation between their characteristics. In this way, the remuneration is adapted to different player types or groups. K-means [12,13] is used to perform the consumers' clustering process. K-means maximizes the distance between different clusters while keeping each observation (consumer) as close as possible to the center of the respective cluster (1).

$$\min \sum_{i=1}^{k} \sum_{x \in c_i} \|x - \mu_i\|^2 \tag{1}$$

where μ_i is the mean of points in C_i, *i.e.* the cluster *centroid*.

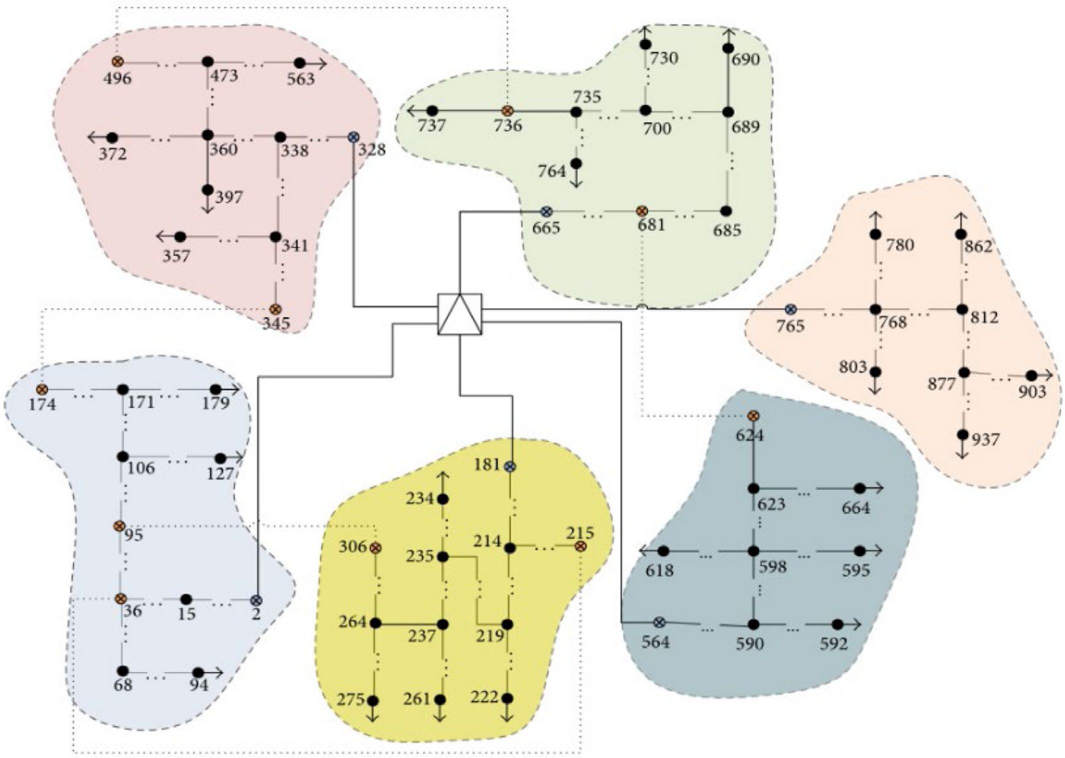

Fig. 2. Considered distribution network [9].

The proposed remuneration methodology is based on the calculation of remuneration schemes and on the evaluation of income for the aggregated consumers from providing flexibility. The defined remuneration method is based on different consumers' characteristics, as explained below. The remuneration value fluctuates according to a factor that comprises the different variables that influence the remuneration calculation. The income analysis considers the different methods: method *A* considers the demand response remuneration price *CDR*; method *B* considers *CDR* affected by the consumers' elasticity; and method *C* also considers elasticity and increment or decrement to the consumption value.

The formulation is summarized as follows. The equation presented in (2) is used to represent the remuneration calculation for each consumer. In (2) CDR_c represents the remuneration of the consumers, obtained through the proposed methodology. The *Factor* consists in several components and influences the variable CDR that represents the cost of reduction (when the consumer is paid to reduce consumption). In (3) P_RTPDR_MAX represents the maximum value of reduced energy per consumer, $P\_RTP\_initial$ represents the initial consumption of each load, *Gen* is the system production and Elast represents the elasticity of each consumer. w, x, y, z, where $w+x+y+z=1$ are weights that can be assigned to the several variables, endowing them a relative importance.

$$CDR_c = CDR \times Factor \tag{2}$$

$$Factor = w \times P_{RTPR_{MAX}} + x \times P_{RTP_{initial}} - y \times Gen - z \times Elast \tag{3}$$

The formulation presented in (4) is used to represent the income associated at each consumer after applying the remuneration methods. CDR_c represents the value of remuneration obtained by applying the proposed model, *Preduct_RTPMAX* represents the maximum consumption reduction for participation in Real-Time Pricing (RTP) demand response programs.

$$Income_{(€)} = CDR_{c(u.m./kWh)} \times Preduct\_RTPMAX_{(kWh)} \tag{4}$$

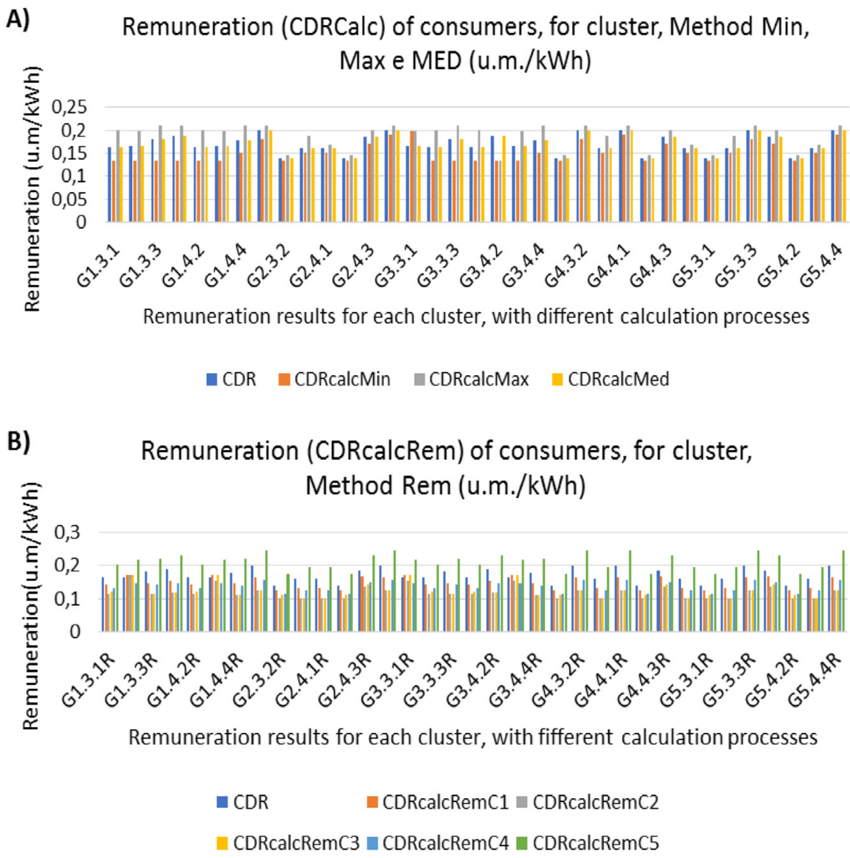

Fig. 3. Remuneration values obtained with (A) Method Min, Max and Med and (B) Method Rem.

3. Results

This section shows the results that can be achieved using the proposed methodology for remuneration definition. This case study considers a real distribution power network (Fig. 2) that includes 30 buses, supplied by one high voltage substation (60/30 kV) with a total number of 937 buses and 464 MV/LV transformers, with 20 310 consumers and 548 distributed generators. [14]. This power network is composed by several areas, which refer to different operation zones of the VPP that manages this network. The clustering process is, however, applied to all consumers, regardless of the operation area, so that the remuneration and tariffs can be defined for all the considered consumers.

The calculation of the remuneration (CDR_c) is carried out by applying different forms of remuneration. The first three methods, for baseline results, consider as remuneration values, the maximum, minimum and average initial cost of consumption reduction, according to all players that compose each cluster/group of consumers. The fourth method refers to the proposed remuneration approach.

The chart presented in Fig. 3(A) shows that, when compared with the *CDR*, the calculated CDR_c have the expected behavior. When it is calculated using the minimum cost value from the cluster, the remuneration is lower compared to *CDR*. Using the maximum cost from the cluster, the calculated CDR_c reaches a higher value than the basis *CDR*. Finally, when considering the average cost from the cluster, then $CDR_c = CDR$.

From Fig. 3(B) it is important to analyze the remuneration values obtained, since the weights *w, x, y* and *z* have a significant influence on the remuneration values. The distinct values assigned to the weights enable adapting the remuneration values according to the current situation of the system (renewable generation at each time) and the consumers' characteristics.

The automatic adaptation of the remuneration values enables the aggregator to manage the overall cost for each cluster, according to the aggregator needs, while guaranteeing a fair remuneration for the consumers according to their characteristics and participation, and also according to the needs from the system.

4. Conclusions

The current energy transition is being pushed by the increase of renewable energy generation and is driving consumers to take an active role in power and energy systems. In order to take full advantage from the full potential of consumers' flexibility, it is essential that suitable models for consumers' participation remuneration are defined.

The decision support model for consumers' flexibility remuneration proposed in this paper enables attracting consumers to assume a more active role in the system, through fairer remuneration strategies, which consider consumers' characteristics and the generation of energy associated with the whole system. In this way, the proposed model enables finding suitable groups of consumers associated to a common aggregator, according to the similarity of their characteristics, using a clustering approach; and to determine an adaptive remuneration price for consumers' flexibility, considering the market prices, the energy production and the willingness of each consumer to participate in demand response programs.

As future work, RemT will be integrated in the Multi-Agent based Real-Time INfrastructure for Energy (MARTINE) laboratorial platform, located at GECAD/ISEP, to be used as flexibility remuneration definition model for consumers' acting in diverse levels of power and energy systems, and participating in different demand response models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work has received funding from the EU Horizon 2020 research and innovation program under project TradeRES (grant agreement No 864276). The work has been done also in the scope of project UIDB/00760/2020, and CEECIND/01811/2017, financed by FEDER Funds through COMPETE program and from National Funds through (FCT).

References

[1] European Commission. Clean energy for all Europeans. Euroheat Power 2019;14(3). http://dx.doi.org/10.2833/9937.
[2] Gencer B, Larsen ER, van Ackere A. Understanding the coevolution of electricity markets and regulation. Energy Policy 2020;143:111585. http://dx.doi.org/10.1016/j.enpol.2020.111585.
[3] Dranka GG, Ferreira P. Load flexibility potential across residential, commercial and industrial sectors in Brazil. Energy 2020;201:117483. http://dx.doi.org/10.1016/j.energy.2020.117483.
[4] Tjørring L, Jensen CL, Hansen LG, Andersen LM. Increasing the flexibility of electricity consumption in private households: Does gender matter? Energy Policy 2018;118:9–18. http://dx.doi.org/10.1016/j.enpol.2018.03.006.
[5] Pinto T, Faia R, Ghazvini MAF, Soares J, Corchado JM, Vale ZMA, do. Decision support for small players negotiations under a transactive energy framework. IEEE Trans Power Syst 2018;1. http://dx.doi.org/10.1109/TPWRS.2018.2861325.
[6] Ringler P, Keles D, Fichtner W. Agent-based modelling and simulation of smart electricity grids and markets - a literature review. Renew Sustain Energy Rev 2016;57:205–15. http://dx.doi.org/10.1016/j.rser.2015.12.169.
[7] Pinto T, Wooldridge M, Vale Z. Consumer flexibility aggregation using partition function games with non-transferable utility. IEEE Access 2021;(1). http://dx.doi.org/10.1109/ACCESS.2021.3069416.
[8] Raiker GA, Subba Reddy B, Umanand L, Agrawal S, Thakur AS, Ashwin K, Barton JP, Thomson M. Internet of things based demand side energy management system using non-intrusive load monitoring. In: 2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020). 2020, p. 1–5. http://dx.doi.org/10.1109/PESGRE45664.2020.9070739.
[9] Ribeiro C, Pinto T, Vale Z, Baptista J. Data mining for remuneration of consumers demand response participation. In: De la Prieta F, Mathieu P, Rincón Arango JA, El Bolock A, Del Val E, Jordán Prunera J, Carneiro J, Fuentes R, Lopes F, Julian V, editors. BT - Highlights in Practical Applications of Agents, Multi-Agent Systems, and Trust-Worthiness. the PAAMS Collection. Cham: Springer International Publishing; 2020, p. 326–38.
[10] Ribeiro C, Pinto T, Vale Z, Baptista J. Data mining for prosumers aggregation considering the self-generation. In: Omatu S, Rodríguez S, Villarrubia G, Faria P, Sitek P, Prieto J, editors. Distributed Computing and Artificial Intelligence, 14th International Conference. Cham: Springer International Publishing; 2018, p. 96–103.
[11] Pinto T, Morais H, Oliveira P, Vale Z, Praça I, Ramos C. A new approach for multi-agent coalition formation and management in the scope of electricity markets. Energy 2011;36:5004–15. http://dx.doi.org/10.1016/j.energy.2011.05.045.
[12] Jain AK. Data clustering: 50 years beyond K-means. Pattern Recognit Lett 2010;31:651–66.
[13] Li S, Ma H, Li W. Typical solar radiation year construction using k-means clustering and discrete-time Markov chain. Appl Energy 2017;205:720–31. http://dx.doi.org/10.1016/j.apenergy.2017.08.067.
[14] Faria P, Soares J, Vale Z, Morais H, Sousa T. Modified particle swarm optimization applied to integrated demand response and DG resources scheduling. IEEE Trans Smart Grid 2013;4:606–16. http://dx.doi.org/10.1109/TSG.2012.2235866.